LEVEL II

AD A078085

D D C
RECEIVED
DEC 3 1979
E

DDC FILE COPY

UNIVERSITY OF MARYLAND
COMPUTER SCIENCE CENTER

COLLEGE PARK, MARYLAND
20742

79 11 30 008

DAAG53-76-C-Ø138, DARPA Order-32Ø6

1

14 TR-763
DAAG-53-76C-0138

11 May 1979

6 TEXTURE PRIMITIVE EXTRACTION USING AN EDGE-BASED APPROACH.

12 34

10 Tsai-Hong Hong,
Charles R. Dyer
Azriel Rosenfeld

Computer Science Center
University of Maryland
College Park, MD 20742

9 Technical rept.,

ABSTRACT

Many textures are characterizable as a collection of primitive elements arranged over a background field. This paper defines an edge-based procedure for extracting primitives from textures. The technique groups edges into region boundaries by joining facing pairs of edge points. A pilot evaluation is performed by examining the usefulness of these primitives for texture classification.

The support of the Defense Advanced Research Projects Agency and the U.S. Army Night Vision Laboratory under Contract DAAG-53-76C-0138 (DARPA Order 3206) is gratefully acknowledged, as is the help of Kathryn Riley in preparing this paper.

403 018

JOB

1. Introduction

The structural approach to texture analysis consists of the extraction of meaningful texture primitives, defined as connected regions satisfying certain properties, and the description of these primitives in terms of their attributes and spatial interrelations. This model of texture as a segregation of the visual field into primitives has considerable psychophysical support; see, e.g., Beck's similarity grouping experiments [1] and Julesz' work on cluster detection in random patterns [2].

The descriptive and organizational aspects of the texture problem given a set of primitives have been studied in order to explore placement rule properties used in discrimination. O'Callaghan [3] developed techniques for finding the perceptual boundaries in dot patterns and Stevens [4] used the same domain to locate locally parallel strings of dots. Others have used edges as primitives, investigating both synthetic and real-world texture discriminability using statistical measures of the first order (e.g., edge per unit area [5,6] and the ratio of edge orientation to length per unit area [7]) or second order (e.g., generalized cooccurrence matrix features from edge orientation [8]). These last methods are more structural-statistical hybrid approaches, however, than purely structural ones.

To date, texture primitive extraction methods have been predominantly region-based, emphasizing gray level grouping rules for defining areas which are homogeneous with respect to brightness. Tsuji and Tomita [9] define primitives as connected components of constant gray level. Maleson et al. [10] use a priori defined simple convex polygons of various sizes, shapes, and orientations as primitives, choosing the maximal best fit based on gray level constancy. Wang et al. [11] extract primitives by various thresholding schemes, each connected component of above threshold points defining a region.

While edge-based methods have been previously used in statistical approaches to texture (see above), the dual to region-based primitive extraction, i.e., edge grouping for delimiting regions by their boundaries, has not been adequately studied. Strong and Rosenfeld [12] developed a technique using a *propagation process* for coloring in region interiors from edges. Marr's primal sketch is computed (in part) by grouping edge and line detector outputs into long segments (this procedure is called "curvilinear aggregation") [13], but the representation stops short of producing closed curves, delaying their extraction until information about the depth, orientation and discontinuities of visible surfaces is made explicit in the $2\frac{1}{2}$-D sketch. Zucker et al. [14] argue, on the other hand, that edges can often be used to delineate physical objects without such higher level knowledge.

In this paper we address the texture primitive extraction problem using an edge-based technique. Primitives are defined as areas which are enclosed by edges, thus delimiting elements by their boundaries rather than by properties of their interiors. The method is evaluated in a pilot study in which a few texture samples, taken from Brodatz [15] textures and three LANDSAT geological terrain types, are clustered using first-order statistics of region properties only.

2. Primitive extraction by edge point grouping

2.1 The approach

Methods for edge point grouping have been developed primarily for the purposes of locating curves and streaks in images. Both sequential tracking and parallel grouping techniques have been devised (see [16] for a survey). For the most part, two Gestalt heuristics are used for combining unit edge segments into long chains: edges which are proximal and represent good continuation are locally consistent; other configurations are inconsistent.

In texture primitive extraction, boundaries are known to form closed contours, so we can add the *heuristic of closedness*. In the continuous case, each point p on the boundary of a primitive has a corresponding (nearest) boundary point q which is on the opposite side of the region and is defined as follows. Consider the ray with origin at p and orientation perpendicular to the tangent line through p and towards the region's interior. This ray must intersect the boundary again; q is defined to be the nearest such intersection point. Two properties of this definition are of interest. First, the relation "is an opposite boundary point to" is not symmetric. Second, the line segment $\overline{pq}$ must be entirely contained in the region. Figure 1 illustrates this configuration.

In digital images, region boundaries are indicated locally by gray level discontinuities and are detectable by any of a variety of edge-detection operators. In this case, the analog of an opposite boundary point pair is a pair (x,y) of antiparallel edge points such that y is the closest edge point in the gradient direction from x on x's dark side.

Given an image from which a set of antiparallel edge pairs have been determined, the boundary formation problem is now reformulated as how to group these pairs according to the areas they surround. There are several possible ways of grouping edges into boundaries from the descriptions associated with antiparallel pairs, e.g., using their locations, orientations, and separations. One possibility would be to cluster the midpoints of the pairs' line segments as they should form a kind of medial axis for the region. However, since even in ideal figures these midpoints need not be connected (see Figure 2), this approach does not seem promising.

A second method is to group edge pairs based on the intersections of the line segments that join antiparallel pairs. A pixel is regarded as a possible interior point of a primitive if it is on the line segment joining a pair of antiparallel edge points. In practice, due to the presence of noise, giving rise to missing and spurious edges, each pixel's likelihood of being an interior point can be measured by the number of times that it occurs on line segments joining antiparallel pairs. We now describe in more detail the algorithm which implements this method of primitive extraction.

2.2 The algorithm

The algorithm for extracting dark primitives occurring on a light background consists of several steps. Its description will now be given in conjunction with its step by step performance on two small data sets. The first is a set of terrain samples from a LANDSAT image of eastern Kentucky. Four 128 by 128 images were chosen from each of three geological terrain types, as shown in Figures 3a, 4a, and 5a. A second data set was taken from four of the texture types in Brodatz [15]; the images are shown in Figures 6a, 7a, 8a, and 9a.

The first step of the algorithm locates edges by applying an edge detection operator to the image, followed by thresholding to eliminate weak edges, and non-maximum suppression to delete redundant responses to a single boundary. In this way we obtain a "cleaned" edge map of potential boundary points on which to do further processing.

In our experiments we have used a set of eight 3 by 3 masks as shown in Figure 10 to determine the edge response at each point. Edge magnitude is equal to the maximum response and edge direction is taken parallel to the orientation of the corresponding detector. Points with edge magnitude less than a threshold t were then set to zero; for the terrain textures we used t=6 and with the Brodatz textures, t=3. These values of t were chosen by hand; in general t should be chosen based on the expected contrast of the primitives with the background. Non-maximum suppression used a 1 by 3 neighborhood centered on each point and oriented in the direction perpendicular to the edge at that point. A point's edge magnitude was set to zero if either neighbor had a larger edge magnitude. The result of this step for the two data sets is shown as part b in Figures 3-9.

In the next stage, antiparallel edges are paired and region interiors are filled in as follows. At each edge point a search is made of the pixels on the ray oriented in the direction perpendicular to the edge's orientation and towards the edge's dark side. If the first edge encountered is antiparallel* to the edge point at the ray's origin, then every point on the line segment joining the pair should be in the interior of a primitive. Given an output array with dimensions equal to those of the input picture , this pairing is recorded by incrementing each of the output bins corresponding to points on the line segment. This process is carried out for all edge points in the image. Notice that if the search space is exhausted without finding an edge point, or an edge with improper orientation is found, then no contribution is made to the output array from the given edge point.

Other search strategies for an edge's antiparallel point(s) could also have been used, for example based on a sector emanating from the edge. The simple one used here proved sufficient for

---

* If an edge with orientation 45i° is labeled i, then define two edges with labels i and j to be <u>antiparallel</u> if j=i+3 mod 8, i+4 mod 8, or i+5 mod 8.

this pilot study. If specific knowledge is available about the expected size, shape, or orientation of primitives, then further refinements of the search space could also be made. For example, the maximum distance searched along the ray should be determined by the maximum diameter of a primitive. For the textures used here, search distance was limited to ten pixels.

The output array from stage two can be interpreted as a function measuring the confidence that each point is part of a primitive. Using this array, the final stage of the algorithm produces a binary mask representing the primitives. There are two ways of deciding that a point p is part of a primitive. First, if p and most of its eight neighbors are confident of belonging to a primitive, then p is called a primitive point. Specifically, let the values of the points surrounding point p be

$$\begin{matrix} a_1 & a_2 & a_3 \\ a_8 & a_0 & a_4 \\ a_7 & a_6 & a_5 \end{matrix} \quad \text{where } a_0 \text{ is the value of p.}$$

For each a_i let $v_i = \begin{cases} 0, & \text{if } a_i=0 \\ 0.1, & \text{if } a_i=1 \\ 0.2, & \text{if } a_i=2 \\ 0.5, & \text{if } a_i=3 \\ 1.0, & \text{otherwise} \end{cases}$

Then point p is a primitive point if $\sum_{i=1}^{8} v_i \geq 1$.

Since this weighting scheme is biased against points which are on the border of a primitive, a weak region growing step is next applied in order to add such points to the primitives. Specifically, if a point p is adjacent to a primitive point q and the gray levels at these two points are identical, then p too is called a primitive point. This procedure also fills in small holes in primitive elements. The primitives extracted by this method are displayed as part c in Figures 3-9.

3. Evaluation

The regions extracted by the procedure described in Section 2 for the textures shown in Figures 3-9 appear to be reasonable primitives. A further test was conducted to evaluate their usefulness for texture classification. In this test first-order statistics of the primitives in the two data sets were measured and plotted in order to subjectively determine the separability of the classes. Six properties of the primitives were measured: area, perimeter, dispersedness, elongatedness, eccentricity, direction of major axis, and average gray level.

The area of a primitive is defined to be the number of pixels comprising the region. Perimeter is the number of boundary pixels. Dispersedness is defined as the ratio of the square of the perimeter to the area. Eccentricity is defined as the ratio of a primitive's major to minor axis of inertia; and direction of major axis is the angle that the major axis makes with the vertical. See [11] for more detailed descriptions of these properties.

Following Wang et al. [11], two features were derived from each property value histogram for each texture window as descriptors of the texture. Specifically, for each property and each image the mean and standard deviation of the values for all primitives with area greater than 9 were computed. These feature values are plotted in Figures 11 and 12 for the terrain and Brodatz texture data sets, respectively.

For the Brodatz texture samples, those features which separated the four types best are seen to be: mean of primitive area, mean of perimeter, and standard deviation of average gray level. In each case the four classes are separated or nearly separated from each other. The separability of features derived from the terrain textures was less clear-cut, but the standard deviation of area feature did nearly distinguish all three types. Several other features separated two of the terrain types. These results are summarized in Table 1.

In conclusion, this pilot study shows that very simple first-order features discriminate well between the pairs of textures in two separate data sets. These results are better than those obtained using any of the threshold-based extraction schemes proposed in [11].

4. Concluding remarks

A new method of extracting texture primitives based on pairing antiparallel edge points has been described. The success of the approach depends primarily on the sufficiency of the edge map in surrounding the interiors of primitives. In the examples given the procedure proved quite robust in "filling in the gaps" on a primitive's boundary and ignoring noise edge responses. Subjectively, the primitives obtained conform well to meaningful regions in the textures. This is substantiated by the successful results obtained in separating the texture types using first-order statistics derived from these primitives.

The applicability of this technique to the general problem of object extraction is exhibited in Figure 13. Shown are four FLIR images, each containing a single target (visible as a small dark blob), and the results of applying the algorithm to these images. In each case the target was properly extracted. In general, in situations where thresholding-based schemes are inappropriate for segmentation, the method presented here provides a promising alternative.

References

1. J. Beck, Similarity grouping and peripheral discriminability under uncertainty, American J. of Psychology 85, 1972, 1-19.

2. B. Julesz, Visual pattern discrimination, IRE Trans. on Information Theory 8, 1962, 84-92.

3. J. F. O'Callaghan, Computing the perceptual boundaries of dot patterns, Computer Graphics and Image Processing 3, 1974, 141-162.

4. K. A. Stevens, Computation of locally parallel structure, Proc. DARPA Image Understanding Workshop, November 1978, 92-102.

5. A. Rosenfeld and M. Thurston, Edge and curve detection for visual scene analysis, IEEE Trans. on Computers 20, 1971, 562-569.

6. R. Ohlander, Analysis of natural scenes, Ph.D. dissertation, Carnegie-Mellon University, Pittsburgh, Pa., April 1975.

7. B. R. Schatz, The computation of immediate texture discrimination, M.I.T. A.I. Memo 426, M.I.T., Cambridge, Ma., August 1977.

8. L. S. Davis, S. Johns, and J. K. Aggarwal, Texture analysis using generalized cooccurrence matrices, Proc. IEEE Conf. on Pattern Recognition and Image Processing, 1978, 313-318.

9. S. Tsuji and F. Tomita, A structural analyzer for a class of textures, Computer Graphics and Image Processing 2, 1973, 216-231.

10. J. T. Maleson, C. M. Brown, and J. A. Feldman, Understanding natural texture, Proc.DARPA Image Understanding Workshop, October 1977, 19-27.

11. S. Wang, F. R. D. Velasco, and A. Rosenfeld, A comparison of some simple methods for extracting texture primitives and their effectiveness in texture discrimination, Computer Science Technical Report TR-759, University of Maryland, College Park, Md., April 1979.

12. J. P. Strong and A. Rosenfeld, A region coloring technique for scene analysis, C.ACM 16, 1973, 237-246.

13. D. Marr, Early processing of visual information, M.I.T. A.I. Memo 340, M.I.T., Cambridge, Ma., December 1975.

14. S. W. Zucker, A. Rosenfeld, and L. Davis, General-purpose models: expectations about the unexpected, Proc. Fourth International Joint Conference on Artificial Intelligence, September 1975, 716-721.

15. P. Brodatz, Textures: A Photographic Album for Artists and Designers, Dover, New York, 1966.

16. E. M. Riseman and M. A. Arbib, Computational techniques in the visual segmentation of static scenes, Computer Graphics and Image Processing 6, 1977, 221-276.

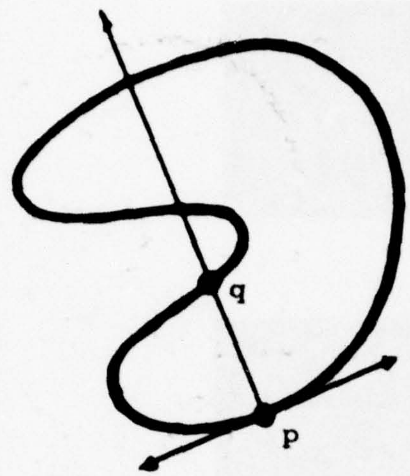


Figure 1. A primitive boundary point p and its opposite boundary point q.

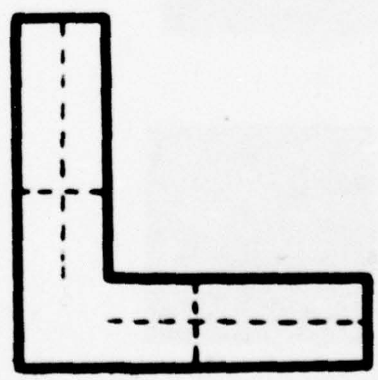
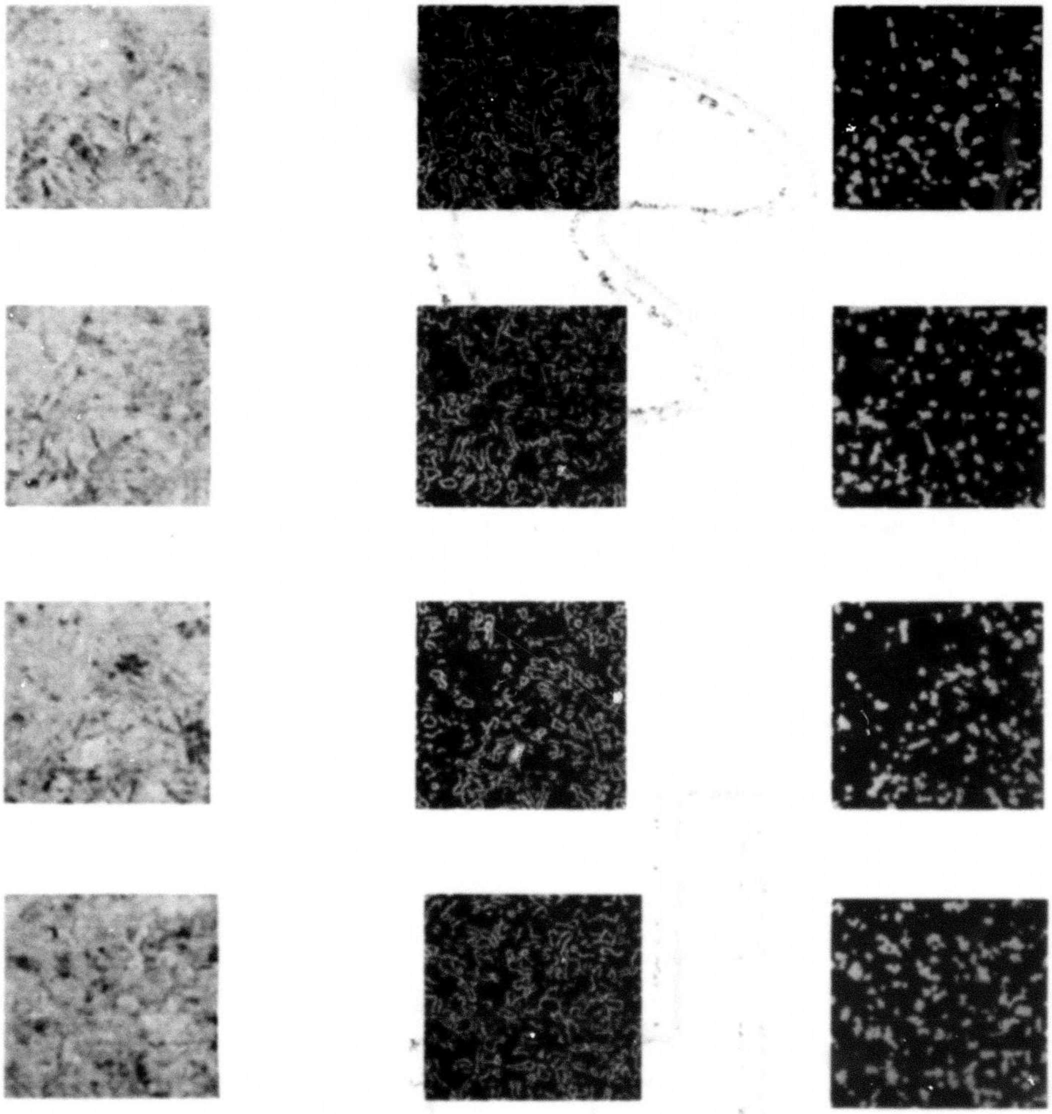


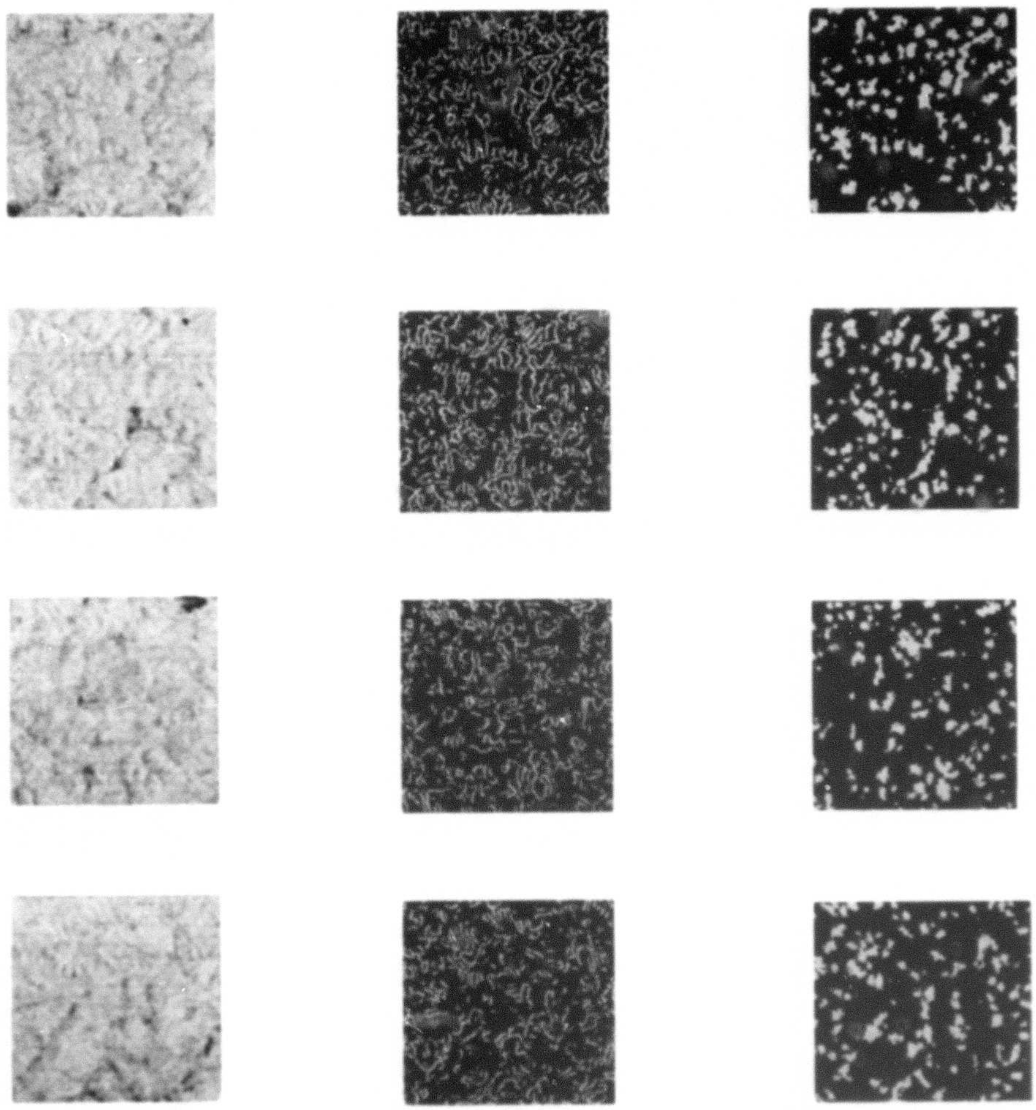
Figure 2. A primitive in which the midpoints of lines joining opposite pairs of boundary points (dotted lines) are not connected.

Best
Available
Copy



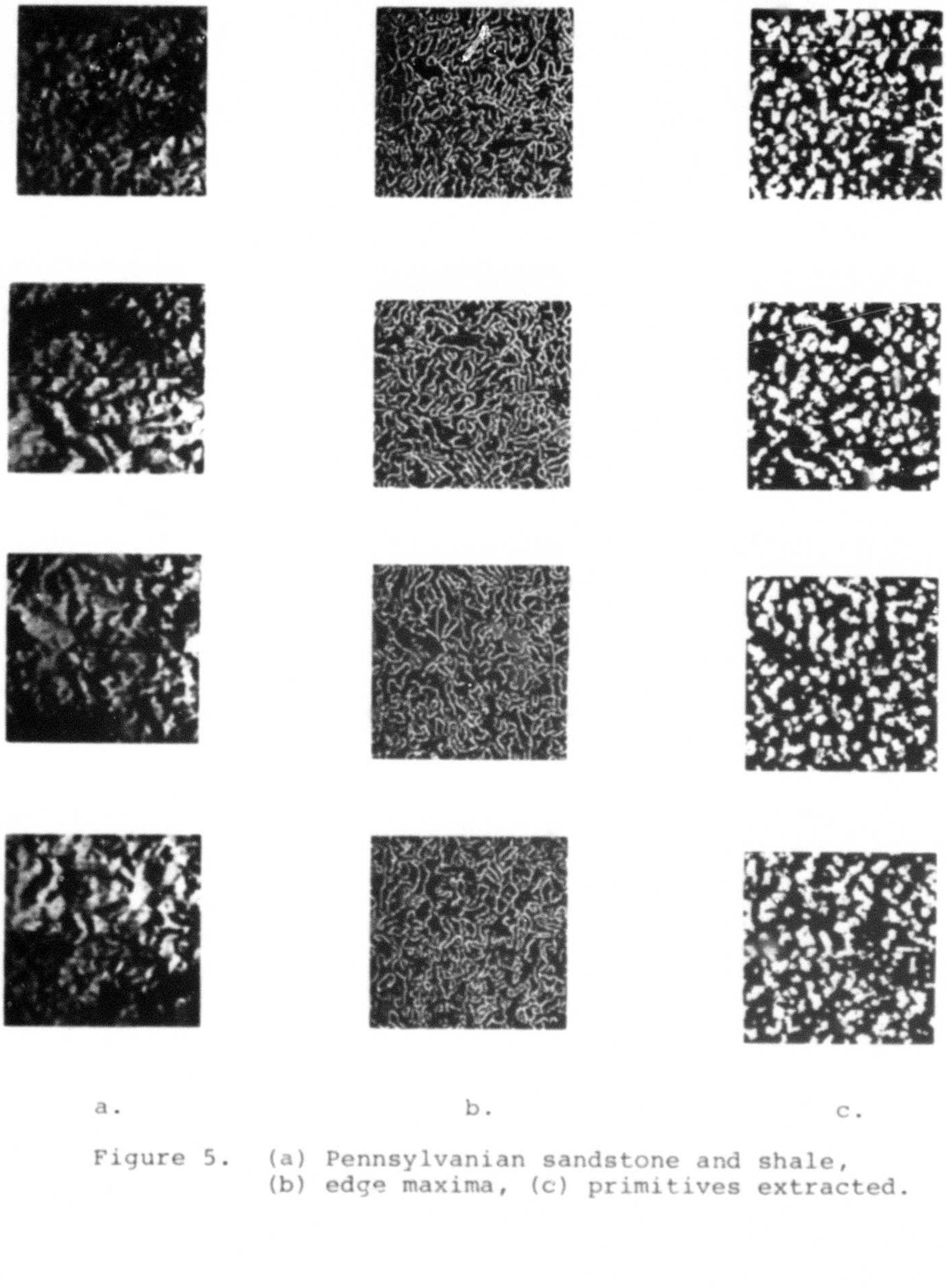
a. b. c.

Figure 3. (a) Mississippian limestone and shale, (b) edge maxima, (c) primitives extracted.



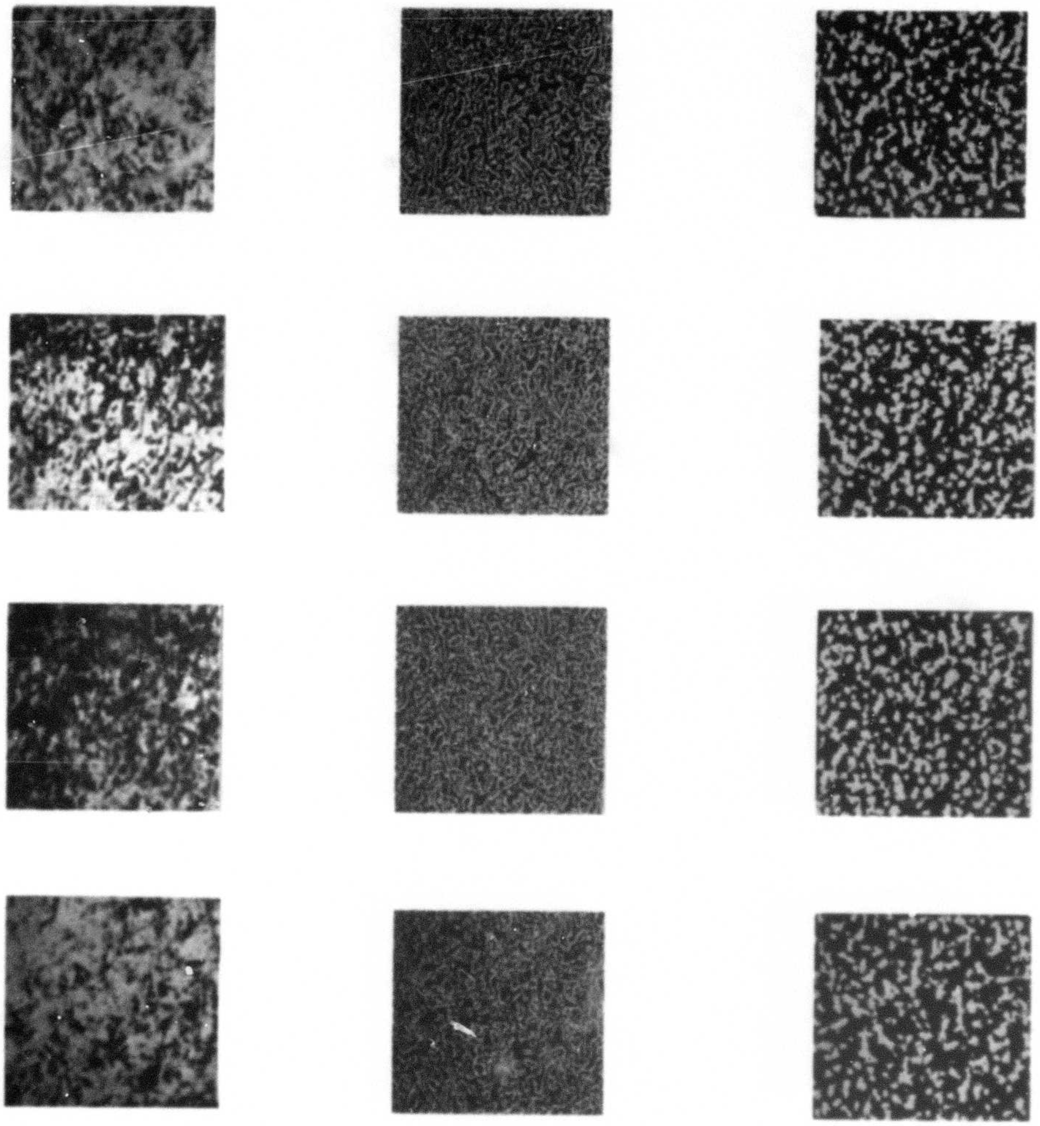
a. b. c.

Figure 4. (a) Lower Pennsylvanian shale,
(b) edge maxima, (c) primitives extracted.



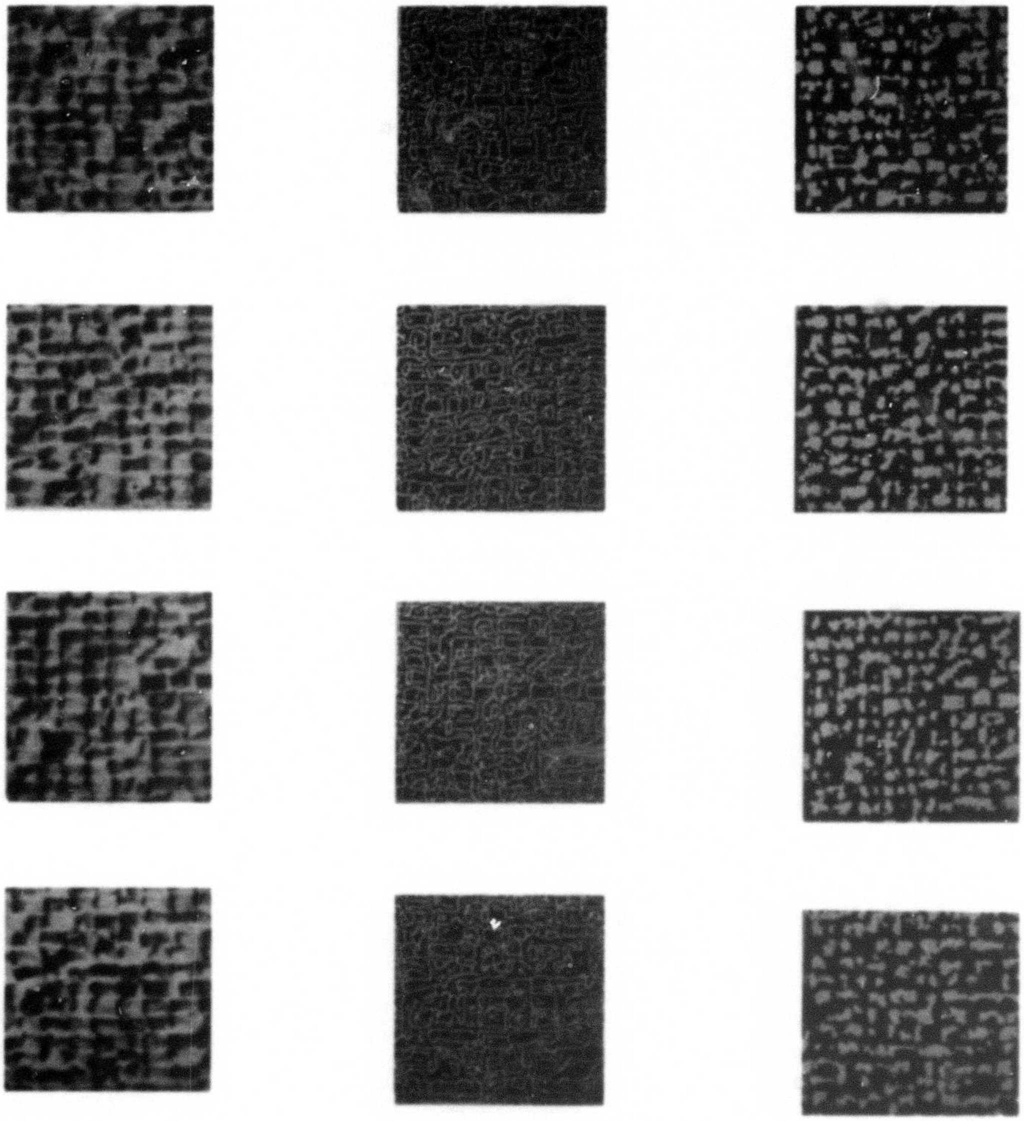
a. b. c.

Figure 5. (a) Pennsylvanian sandstone and shale, (b) edge maxima, (c) primitives extracted.



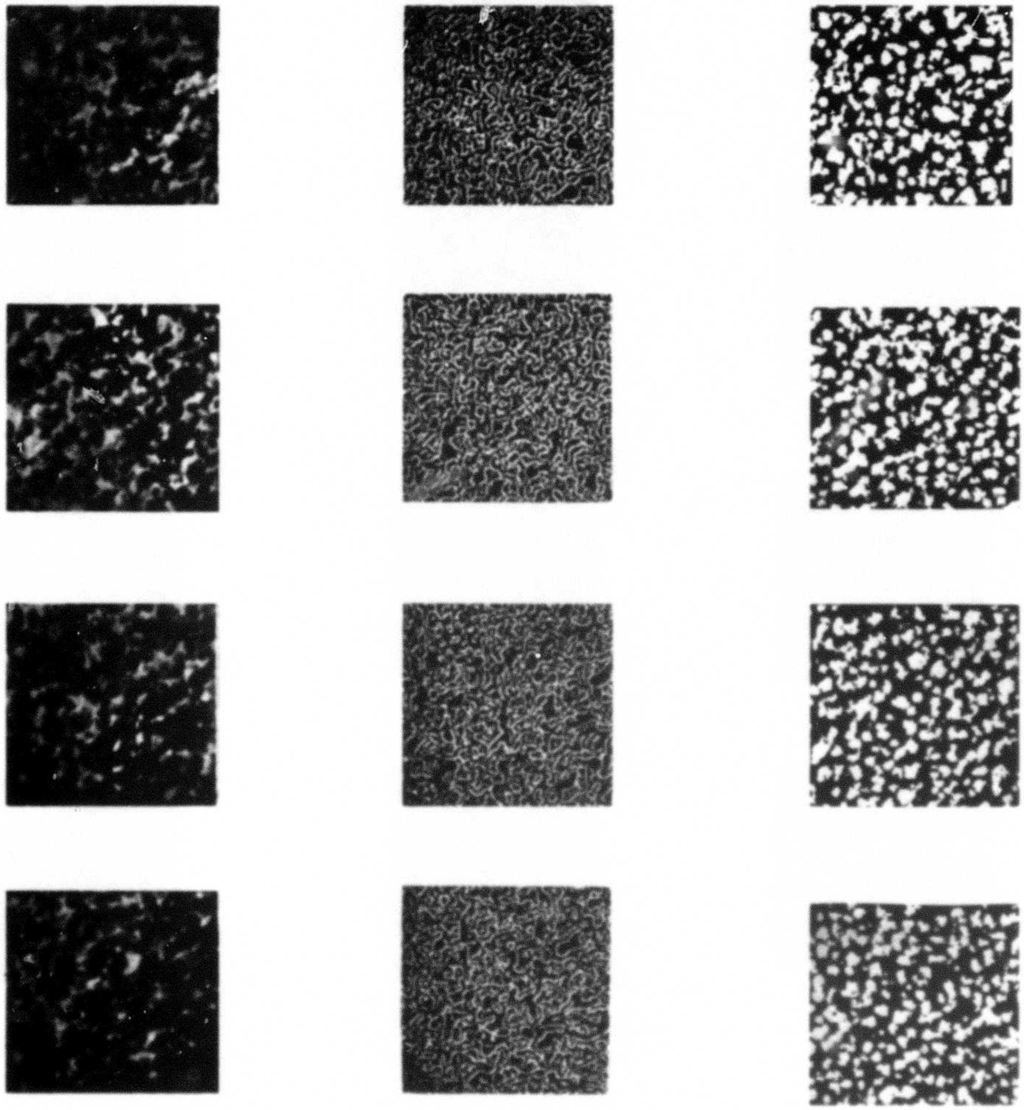
a. b. c.

Figure 6. (a) Grass (plate D9), (b) edge maxima, (c) primitives extracted.



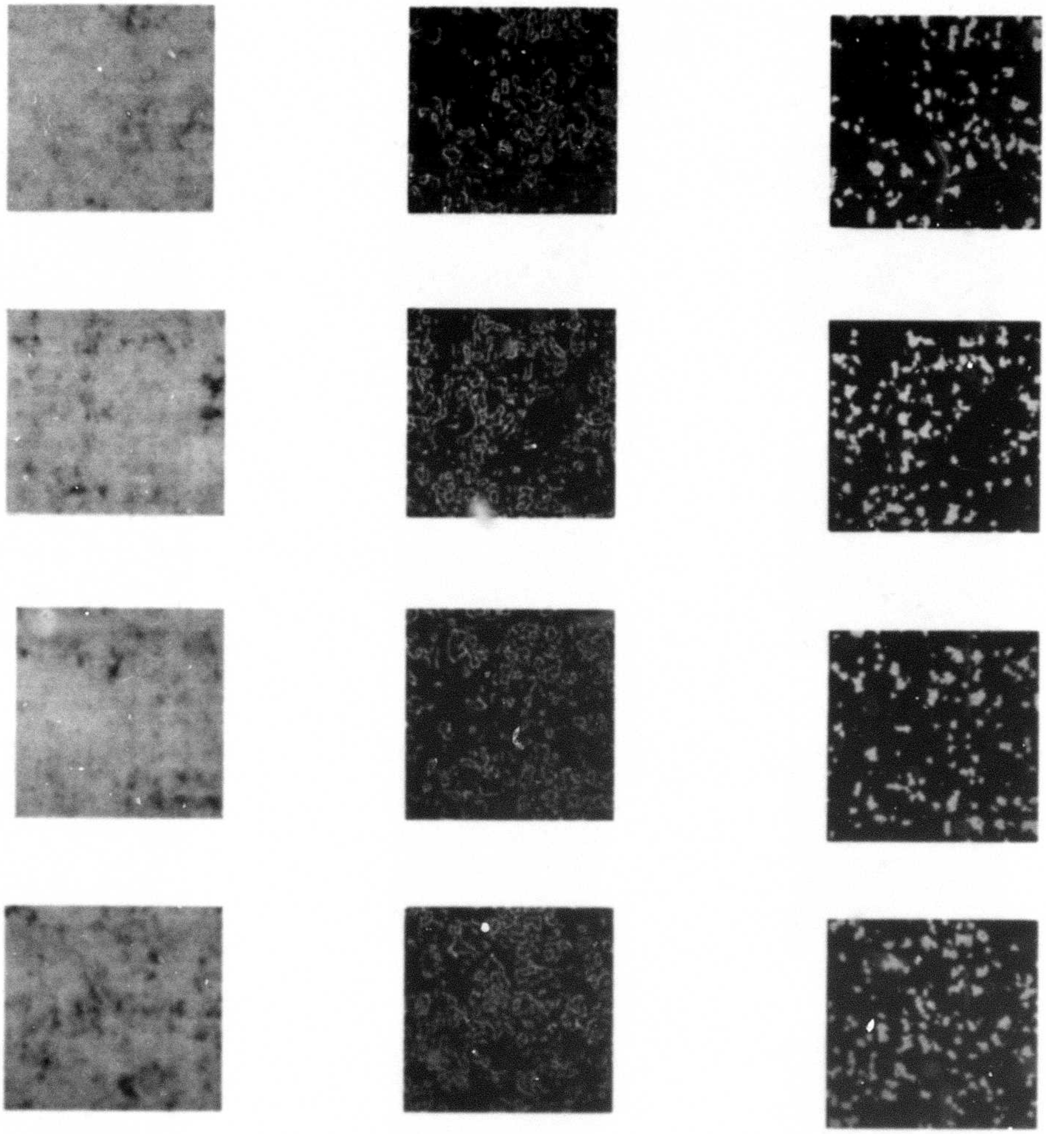
a. b. c.

Figure 7. (a) Raffia (plate D84), (b) edge maxima,
(c) primitives extracted.



a. b. c.

Figure 8. (a) Sand (plate D29), (b) edge maxima, (c) primitives extracted.



a. b. c.

Figure 9. (a) Wool (plate D19), (b) edge maxima, (c) primitives extracted.

Mask	edge direction
1 1 1 0 0 0 -1 -1 -1	0°
1 1 0 1 0 -1 0 -1 -1	45°
1 0 -1 1 0 -1 1 0 -1	90°
0 -1 -1 1 0 -1 1 1 0	135°
-1 -1 -1 0 0 0 1 1 1	180°
-1 -1 0 -1 0 1 0 1 1	225°
-1 0 1 -1 0 1 -1 0 1	270°
0 1 1 -1 0 1 -1 -1 0	315°

Figure 10. 3 by 3 masks used as the edge detection operator.

Figure 11. Features derived from the terrain primitives. L denotes Lower Pennsylvanian shale, M denotes Mississippian limestone and shale, and P denotes Pennsylvanian sandstone and shale.

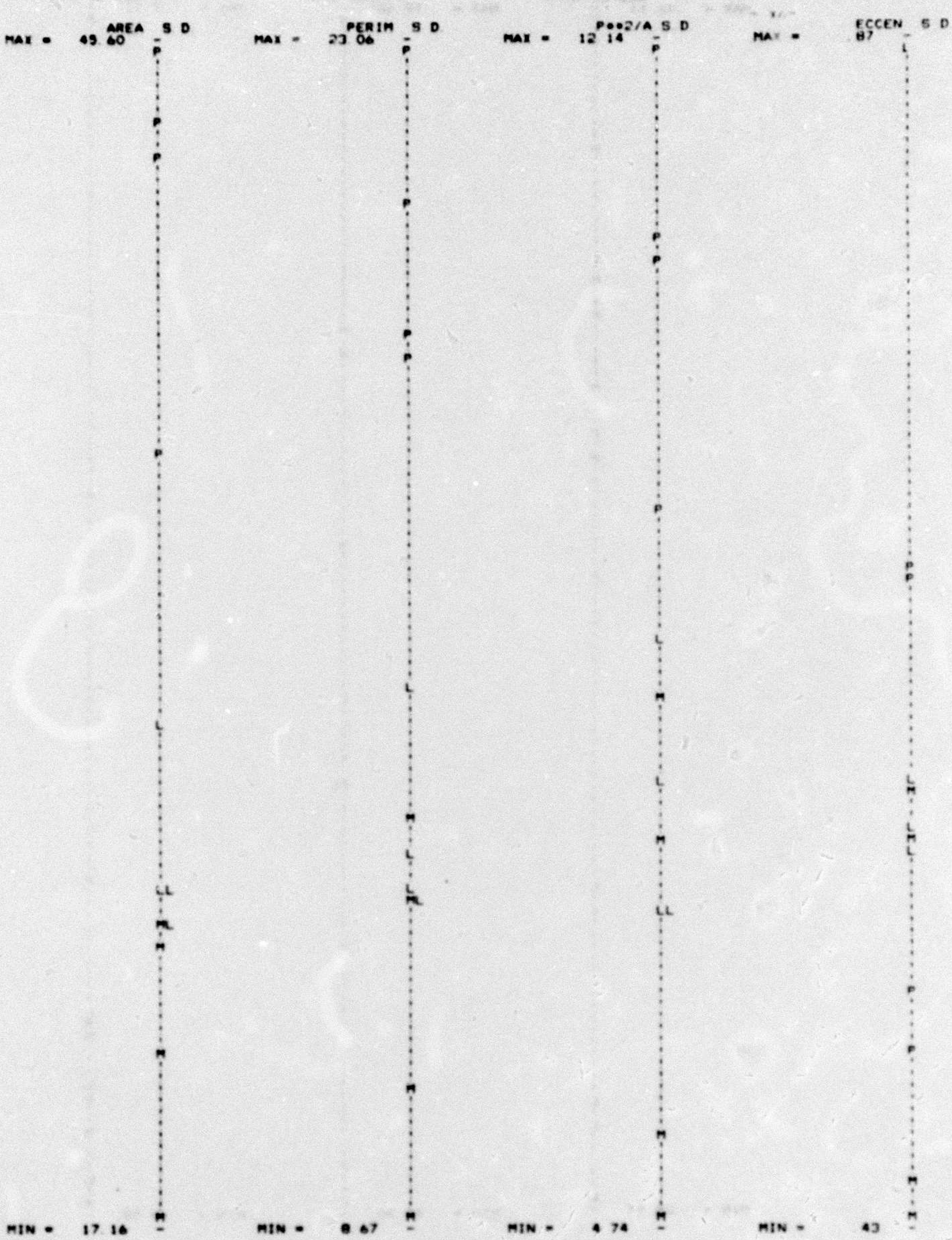


Figure 11. (continued)

Figure 11. (continued)

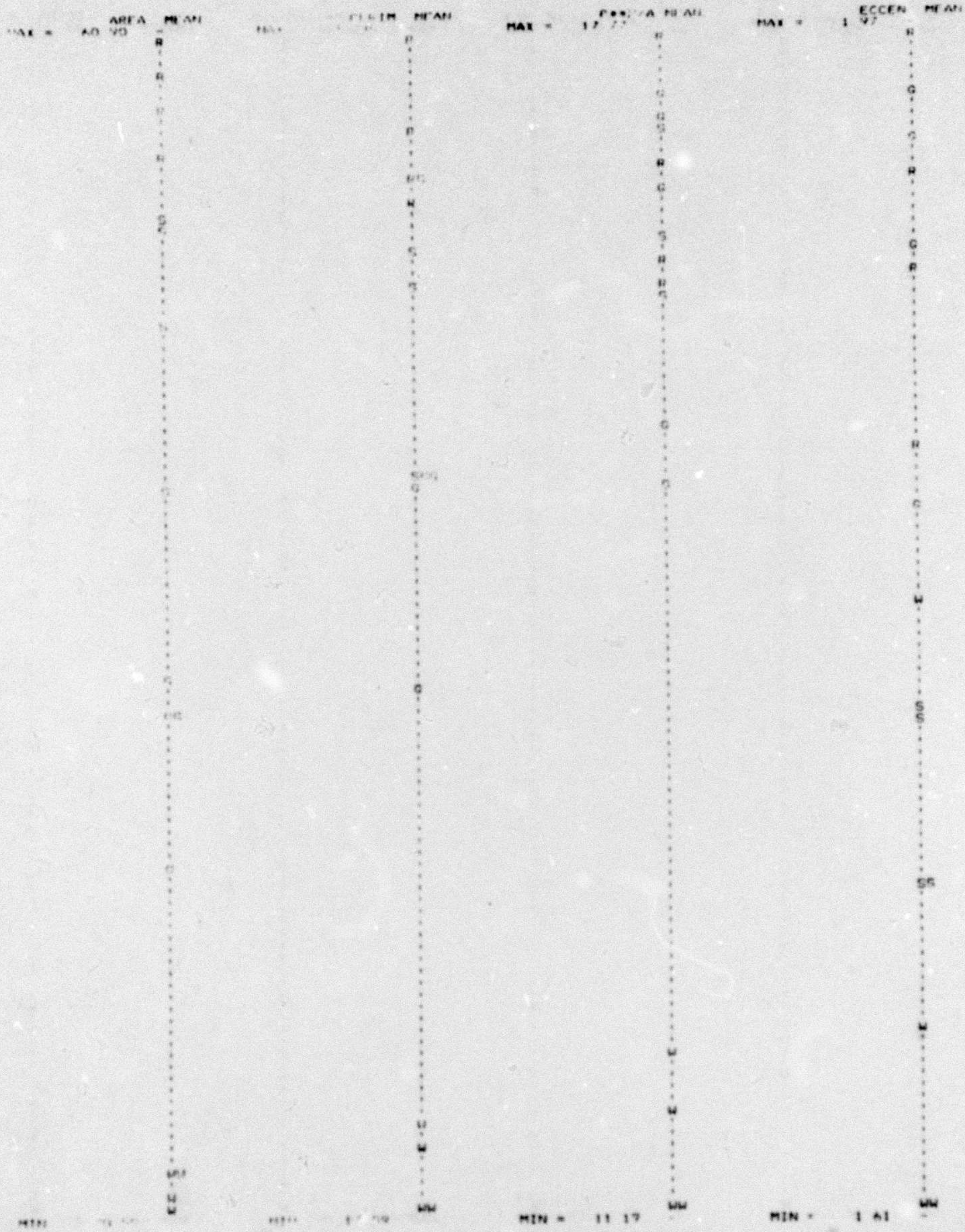
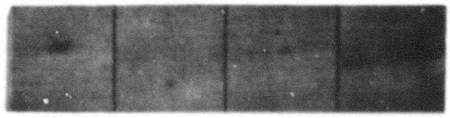


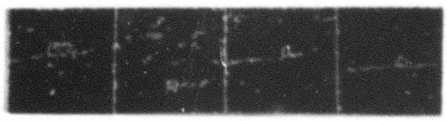
Figure 12. Features derived from the Brodatz texture primitives. G denotes grass, R raffia, S sand, and W wool.

Figure 12. (continued)

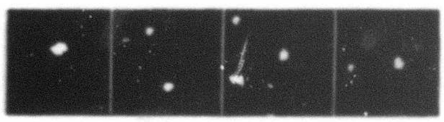
Figure 12. (continued)



a.



b.



c.

Figure 13. (a) Four target windows taken from Forward-Looking InfraRed data base, (b) edge maxima, (c) objects extracted.

Feature	Brodatz textures	Terrain textures
Area mean	R/S/G/W	P/L,M
Area s.d.	R,S,G/W	P/L/M
Perim. mean	R,S/G/W	P/L,M
Perim. s.d.	R,S,G/W	P/L,M
P^2/A mean	R,S,G/W	P/L,M
P^2/A s.d.	R,S,G/W	P/L,M
Eccen. mean	poor	poor
Eccen. s.d.	poor	poor
Orient. s.d.	poor	P,L/M
Gray level mean	R,S/G/W	L/P,M
Gray level s.d.	R/G/S,W	P/L,M

Table 1. Summary of class separability results; "/" means "separates" (ties are considered separable). G denotes grass, R raffia, S sand, and W wool; L means Lower Pennsylvanian shale, M Mississippian limestone and shale, and P Pennsylvanian sandstone and shale.

Unclassified

SECURITY CLASSIFICATION OF THIS PAGE (When Data Entered)

REPORT DOCUMENTATION PAGE		READ INSTRUCTIONS BEFORE COMPLETING FORM
1. REPORT NUMBER	2. GOVT ACCESSION NO.	3. RECIPIENT'S CATALOG NUMBER
4. TITLE (and Subtitle) TEXTURE PRIMITIVE EXTRACTION USING AN EDGE-BASED APPROACH		5. TYPE OF REPORT & PERIOD COVERED Technical
		6. PERFORMING ORG. REPORT NUMBER TR-763
7. AUTHOR(s) Tsai-Hong Hong, Charles R. Dyer, Azriel Rosenfeld		8. CONTRACT OR GRANT NUMBER(s) DAAG-53-76C-0138
9. PERFORMING ORGANIZATION NAME AND ADDRESS Computer Science Center, University of Maryland, College Park, MD 20742		10. PROGRAM ELEMENT, PROJECT, TASK AREA & WORK UNIT NUMBERS
11. CONTROLLING OFFICE NAME AND ADDRESS U.S. Army Night Vision Laboratory, Ft. Belvoir, BA 22060		12. REPORT DATE May 1979
		13. NUMBER OF PAGES 33
14. MONITORING AGENCY NAME & ADDRESS(if different from Controlling Office)		15. SECURITY CLASS. (of this report) Unclassified
		15a. DECLASSIFICATION/DOWNGRADING SCHEDULE

16. DISTRIBUTION STATEMENT (of this Report)

Approved for public release; distribution unlimited.

17. DISTRIBUTION STATEMENT (of the abstract entered in Block 20, if different from Report)

18. SUPPLEMENTARY NOTES

19. KEY WORDS (Continue on reverse side if necessary and identify by block number)

Image processing
Pattern recognition
Texture analysis

20. ABSTRACT (Continue on reverse side if necessary and identify by block number)

Many textures are characterizable as a collection of primitive elements arranged over a background field. This paper defines an edge-based procedure for extracting primitives from textures. The technique groups edges into region boundaries by joining facing pairs of edge points. A pilot evaluation is performed by examining the usefulness of these primitives for texture classification.

DD FORM 1 JAN 73 1473 EDITION OF 1 NOV 65 IS OBSOLETE

Unclassified

SECURITY CLASSIFICATION OF THIS PAGE (When Data Entered)